
Efficient Fruits Classification Using Convolutional Neural Network

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Abstract

Classification of fruits is a growing research topic in image processing. Various papers propose various techniques to deal with the classification of apples. However, some traditional classification methods remain drawbacks to producing an effective result with a big dataset. Inspired by deep learning in computer vision, we propose a novel learning method to construct a classification model, which can classify types of apples quickly and accurately. To conduct our experiment, we collect datasets, do preprocessing, train our model, tune parameter settings to get the highest accuracy results, and then test the model using new data. Based on the experimental results, the classification model of green apples and red apples can obtain good accuracy with little loss. Therefore, the proposed model can be a promising solution to deal with apple classification.

Keywords:

Deep Learning, Convolutional Neural Network, Classification, Apple

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1. Introduction

Apples contain vitamins needed by humans, such as vitamins A, B1, and C that are commonly consumed in large quantities, with more than 80 million tons consumed per year [1]. According to the 2016 global production of fruit by varieties study, apples are the commodity with the third-highest productivity level after watermelon and bananas. China produces the most apples globally, with 44.5 million tons, or about 57.6% of global apple production [2].

Apple classification is a growing research topic that discusses apple scab, apple spot, and apple rot. A paper explored deep learning to establish a classification of apples with the dataset collected from the local market. The paper selected apples from the sample to train their model that can produce a better accuracy score [3].

In the apple classification problem, many studies proposed fruit classification using SVM which uses color, shape, and texture features [11]. However, there remain drawbacks in the large dataset and the difficulty of manual feature extraction. Therefore, the current papers explored various deep-learning approaches to deal with the issues such as CNN [24][25][26].

Current communities proposed artificial intelligence to deal with classification problems including fruit classification. Deep learning has become more popular for constructing effective classification models because massive data and computing resources have doubled in the last few years. The deep learning approach has also obtained some excellent results in the area of image recognition. This suggests that image classification methods can benefit from deep CNN [4].

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In the broad area, several studies of image processing using CNN conducted for real-time facial recognition obtained an accuracy of 89% [6]. A presented classification of apples in images using CNN [7]. A model can adjust the input image. Deformation such as translation, rotation, and scale while reducing the number of parameters. [8]. Based on previous research, CNN can classify those intended for image data so that this research will be used as a classification of apples [9]. A study presented a CNN structure to perform the Apple image classification task. We collected several Apple images from google.com and flagged them for the scarcity of the Apple image dataset. We built a shallow CNN to avoid the overfitting phenomenon, but it still performed well in our test set [5].

Current studies explored the classification of apple species based on imagery using CNN [12]. A paper proposed CNN neural network architecture for automatic apple sorting. Data were trained using the Caffe framework after collecting photos. The trial, which was divided into two cases, confirmed the feasibility of the method. In our test set, the apple image categorization accuracy was about 92 percent when there was no occlusion [10].

Therefore, we propose a novel solution to deal with fruit classification by adopting a deep learning algorithm to detect apple types more quickly and accurately. In research on the classification of apples, our research has the following contributions:

1. We introduce a new technique for classifying fruit types that involves utilizing the CNN algorithm to train apple features and then utilizing a benchmark dataset to develop a viable model. We calculate some citrus features to construct our model, including diameter size, weight, and the RGB average value, all in the feature dataset used in this paper.
2. We construct a novel model to deal with apple classification using a learning technique to produce more accurate and efficient results. To convince our model performance, we present an evaluation metric chart by training a dataset of granny smith and red delicious apples.
3. We test the proposed model to produce an accurate result to achieve a higher accuracy score. The proposed model can distinguish between granny apples and red apples accurately. To achieve the best training model classifier, we tune numerous parameters to acquire the best accuracy value.

Organization: The remainder of this paper the written as follows: Part II delves deeper into related research. Part III explains how this study problem the defined. Part IV describes the experimental setup, including feature learning methodologies, datasets, and data pre-processing, while Part V gives the study's findings and extensive analysis. Part VI summarizes the findings and identifies several unsolved issues in soil classification research.

2. Related Works

Several studies have proposed research using various methods to build a classification model. A learning technique is used to classify photos of rose apples. The best way to set up and operate the system is to collect as many samples as feasible to improve accuracy. Then, to classify rose apples, a database will be constructed. Workplace classification systems are set up in such a way that their accuracy is acceptable. As a result of the trial, the system can achieve a high accuracy of 84.41 percent. This means that the system meets a high level of performance regarding rose apple categorization [13]. In another study, the system was able to classify the types of apples. By using the CNN algorithm, a classification model can produce an effective model to classify the apple type [14].

Another paper proposed a new apple segmentation and recognition method based on an improved Gaussian kernel that combines fuzzy c-means and convolutional neural networks. The importance of determining the distribution characteristics of the data is

analyzed. A convolutional neural network with good self-learning ability was used to study images and extract image features. Meanwhile, the modified fuzzy c-means is used for clustering feature analysis. We changed the radial width selection to improve the functionality of the Gaussian kernel and used it to support the vector engine, which will classify the extracted features. Finally, experiments on Fuji apple images show that the robustness, stability, and accuracy of the proposed algorithm are better than other state-of-the-art representative methods [15].

A new apple leaf disease detection model based on deep CNN is proposed by introducing the Google Net Inception structure and Rainbow merging. Finally, using the long-term test dataset of 26,377 diseased apple leaf photos, the proposed model was trained to detect these five common apple leaf disorders. According to the testing data, the model achieves a detection performance of 78.80%. The findings suggest that the INAR-SSD model solution for early diagnosis of apple leaf disease can identify the disease in real time with greater accuracy and speed than earlier methods [16].

The current paper introduced deep learning for Apple classification using 4,488 for training, 1,928 for verification, and 2,138 for testing. In the paper, they trained 70%, while 30% for validation [17]. Another research proposed the CNN method for automatic fruit classification. The paper collected two color fruit picture collections (public dataset and self-made dataset). The public data set is taken against a sophisticated backdrop. Homemade data sets are taken against a plain background. The paper tuned the parameter and achieved the highest average classification accuracy of 99.8% [18].

Therefore, in this study, we propose a model to handle the classification of apple types based on shape and color by introducing them using CNN. In this experiment, we collected a dataset of an apple image.

3. Proposed Method

In this experiment, we used the CNN algorithm to classify granny smith apples and red delicious apples. In this paper, we express the feature vector as x , and the bias is b . The weight of each feature will be calculated on the vector by multiplying it by the parameter. Equation 1 can be rewritten as equation 2, where x_i is the i -element of the vector x . This function has a *range of* $[-\infty, \infty]$. Table 3.1 describes the mathematical notation of the regularizer.

$$f(x) = x \cdot w + b \quad (1)$$

$$f(x) = x_1w_1 + x_2w_2 + \dots + x_Nw_N + b \quad (2)$$

$$Output = \text{sgn}(f(x)) \quad (3)$$

$$\text{sgn}(x) = \begin{cases} -1 & \text{if } x < 0 \\ 0 & \text{if } x = 0 \\ 1 & \text{if } x > 0 \end{cases} \quad (4)$$

This regression function is used for the classification of categorical classes. we use thresholding, thus, if $f(x) > \text{threshold}$, then it goes to the first class and vice versa $f(x) < \text{threshold}$ goes to the second class. This technique is applied by using the sign (Equation 3) to change the Process value to -1 and 1 as the output (Equation 4), where -1 represents the input that is categorized into the first class and the value 1 represents.

Table 3.1 Mathematical notation of the regularizer

Notation	Description
x	feature vector
b	bias
w	Parameter matrix and vector
x_i	the i -element of vector x
sgn	Output

In this paper, we investigate CNN as a sort of deep learning. In the classification study, the optimizer, activation function, filter size, learning speed, and batch size all affect the accuracy of the CNN model [19]. On the other hand, CNN is a locally connected network [20]. CNN's algorithm has a convolution layer consisting of a set of filters that can be learned, often referred to as kernels [21].

Table 3.2 Mathematical notation of the regularizer

Notation	Description
$x(i) \in R$	Input Features
$x(i) \in Y$ (e. g. $R, \{0, 1\}, \{1, \dots, p\}$)	Outputs
$\theta \in \mathbb{R}^k$	Model Parameters
$h\theta :: \mathbb{R}^n \rightarrow \mathbb{R}$	Hypothetical function
$\ell : \mathbb{R} \times Y \rightarrow \mathbb{R}^+$	Loss Function

In this study, we used the CNN algorithm to classify apple species. Many studies use the CNN algorithm to solve classification problems. We also calculate accuracy and test to get the best results [22]. The following is the formula we use to calculate the model we created:

$$\text{Minimize } \theta \sum_{i=1}^m \ell(h_{\theta}, (x^{(i)}, y^{(i)})) \quad (5)$$

$$f : \mathbb{R}^n \rightarrow \mathbb{R}^m$$

$$z_i(x_i) = w_i x_i + b \quad (6)$$

In this study, the function $h\theta :: \mathbb{R}^n \rightarrow \mathbb{R}$ was made in processing artificial neural networks and will be calculated in CNN assessing the gradient loss function in the model.

4. Experimental Setup

1. Dataset

In this study, we gather a dataset of apples obtained from the Kaggle dataset. We separate the dataset into training and testing data sets. Training data sets are used to create machine learning models, while test data sets are used to test model performance or accuracy. To construct our model, we take a dataset of about 1,312 with 656 red apples and 656 granny apples. We divide the sample into 80% for training and 20% for testing. Table 4.1 depicts a detailed table of the distribution of data sets in the study.

Table 4.1 Details of the distribution of the dataset

Dataset Label	Training	Testing
A	490	166
B	492	164
Total	982	330

2. Data Pre-processing

In this study, preprocessing was carried out using a vectorization process where a process was needed to convert unstructured data into structured data. More than 1400 images of apples to generate vector features. Each label is filled in to determine the data type. Some of these processes are removing the black frame in the image and normalizing the features [23].

3. Classification Method

The dataset is taken from kaggle.com. There are two types of apples, namely Granny Smith apples and Red Delicious apples, in the training folder. Next, the delicious varieties of granny smith apples and red apples are processed into vector shapes first. There are five stages of image classification pre-processing: reading the image, resizing the image, and removing noise, segmentation, and morphology. The idea that will be used for type can be processed in the algorithm. After that, the image pre-processing can be carried out by process testing. In feature extraction, there are two data, namely training data and test data. Then the training data is processed using the CNN algorithm.

This study builds a model for the classification of types of apples by collecting labeled granny and red delicious apples as our dataset. In the processing stage, we perform feature extraction to simplify the process of building a classification model. Vector data is used in the network learning process or studying input data for the modeling process. Then in the validation test, the valid data model will be tested using vector data. To build our model, we construct a novel CNN architecture to build an effective classification.

5. Result & Analysis

This experiment achieved a trade-off between accuracy and performance time by adjusting various hyperparameters to achieve the best network performance. We set epoch = 50 and batch size = 150 during the training and testing phase. The model can classify with the best level of accuracy in the trials that have been carried out. Table 5.1 Training loss and training accuracy result with various epoch-setting

Epoch	Training Loss	Training Accuracy
Epoch 10	0.0025	0.9313
Epoch 20	0.0023	0.9343
Epoch 30	0.0023	0.9378
Epoch 40	0.0023	0.9457
Epoch 50	0.0023	0.9578

Table 5.2 Testing loss and testing accuracy result with various epoch setting

Epoch	Testing Loss	Testing Accuracy
Epoch 20	0.2979	0.9198
Epoch 40	0.2392	0.9466
Epoch 60	0.1800	0.9542
Epoch 80	0.1399	0.9580
Epoch 100	0.0978	0.9885

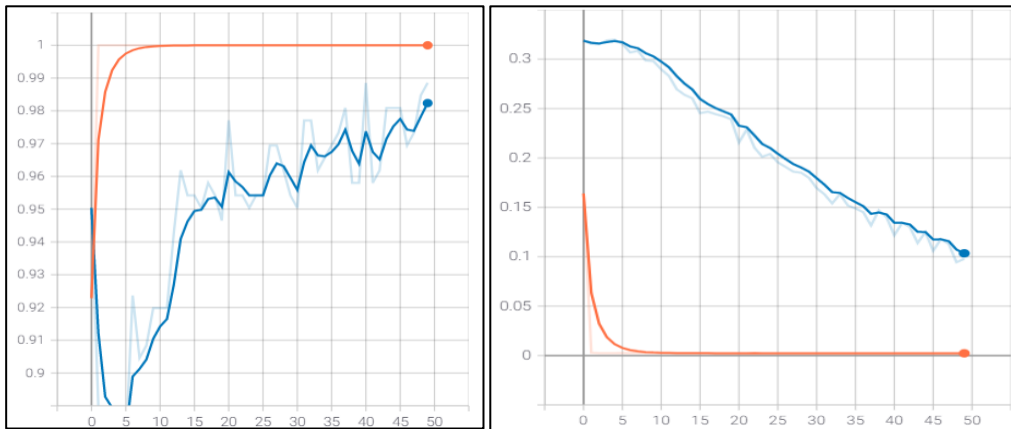


Fig. 1. Training Accuracy and Training Loss

The evaluation matrix is a matrix of the results of the previous training and testing classifications. The matrix classification can be seen in Table 5.3.

Classification Report	Precision	Recall	F1-Score	Support
Apel_grany	0.94	1.00	0.97	131
Apel_red	0.98	0.94	0.97	131
Accuracy	-	-	0.97	262
macro avg	0.97	0.97	0.97	262
weighted avg	0.97	0.97	0.97	262

From Table 5.3, it can be seen that the accuracy or ratio is predicted to have reached 0.97 with each class or type of apple having a positive predictive precision or balance compared to all positive expected results, namely 0.97 for Granny apples and 0,97 for red apples.

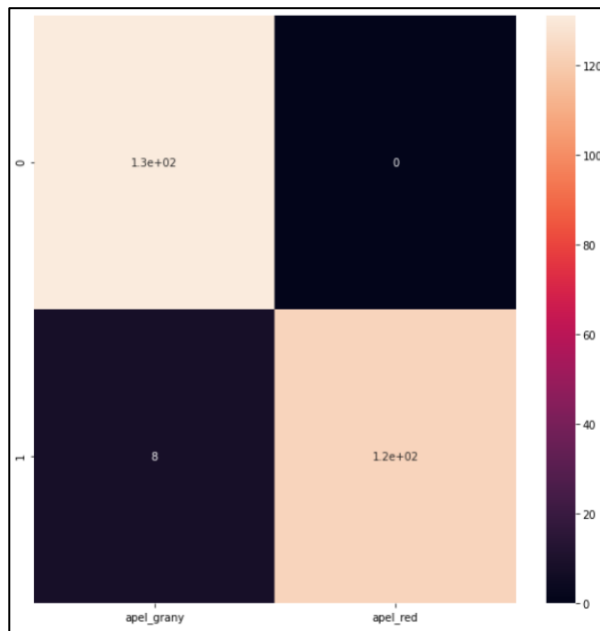


Fig. 2. Confusion Matrix

In this paper, we present a tabular confusion matrix that describes the performance of the model on known test data. Confusion matrix, specifically containing information about True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). Figure 2 shows the evaluation of the metrics with the Confusion Matrix (CM) using the CNN algorithm. From the confusion matrix, we can see the results in the confusion matrix, we get the value of TP = 130, TN = 120, FP = 0, and FN = 8.

6. Conclusion

Effective classification is a fundamental challenge to classify red apples and granny apples. The current techniques adopt traditional machine learning. However, it remains a shortcoming because it is time-consuming and expensive feature engineering. Therefore, to improve the performance of the classification model, this study proposes the CNN algorithm to produce better accuracy and reduce losses in fruit-type classification.

Classification of apples using our proposed model can achieve high accuracy with a tiny loss. To achieve the most effective result, we tune parameters and test the model using new data to measure our model performance. We set epoch = 100, batch size = 150, and split validation = 0.2 during the training and testing phase hyperparameters to optimize network performance. Based on the experiment result, the model can produce an accuracy rate of 97% that quite well helps distinguish apple types.

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